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ESL STUDENTS' PERCEPTIONS OF AI-ASSISTED LEARNING OF ENGLISH LITERATURE: BENEFITS, CHALLENGES, AND ACADEMIC IMPLICATIONS IN SOUTH PUNJAB UNIVERSITIES

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ABSTRACT

Academic environment in undergraduate education in resource-constrained universities has transformed significantly due to the incorporation of the use of artificial intelligence (AI) tools that are specially adjusted to the process of reading, writing, and analyzing literature by students. The study will focus on how English as a Second Language (ESL) students in three state universities in South Punjab, Pakistan, feel regarding the usage pattern of AI tools, preference in platforms, and the academic implication of these tools. The study conducted a survey of 100 ESL students based on a quantitative descriptive-correlational design, and a 25-item Likert-scale questionnaire that was developed by the researcher and has a high internal consistency (Cronbach's α = .87) was used to collect data. The findings showed that the preference was towards ChatGPT (80%), then Meta AI (15%), and the Google Gemini (5%). Despite the fact that 70 percent of students referred to themselves as frequent users, there is still a substantial number of 10 percent who were completely unaware of these tools, signaling the presence of a digital divide that still prevails. The descriptive analysis showed that the means of strong reliance ($M = 4.10$, $SD = 0.65$) and alarming rates of over-reliance ($M = 3.85$, $SD = 0.72$) are high. The multiple regression determination found the use of ChatGPT to be the most positive predictor of academic outcomes ($\beta = .62$, $p = .001$, $R^2 = .52$), and over-reliance was a significant negative predictor ($\beta = -0.31$, $p = .002$). The study expands on the concept of the Performance-Dependency Paradox, according to which, even though AI tools can potentially enhance academic performance, they are also a threat to the development of the ability to independently think critically. Such results are placed in the Technology Acceptance Model (TAM) and are explained in connection with the shortcomings of convenience sampling with suggestions of further stratified, mixed-method studies.

Keywords: *AI-assisted learning, ESL education, ChatGPT, Google Gemini, Meta AI, Technology Acceptance Model, over-reliance, digital divide, South Punjab, academic integrity*

1. INTRODUCTION

1.1 Background

It is observed that over the past few years the academic environment of the Pakistani public universities has radically changed. Students can now use smart phones and talk to the conversational AI to access literary criticism that used to be limited by the limited resources available in departmental libraries. ChatGPT, Meta AI, and Google Gemini platforms have become the main tools of ESL students in South Punjab to study English literature,

instead of a supplement to teaching resources. This change has not been imposed by an institutional strategy on top, but has resulted as a consequence of the overlap of resource shortage and the proliferation of large language models (LLMs).

This is among the avenues that have received a lot of reportage in the recent literature. Zawacki-Richter et al. (2019) followed the history of AI in higher education starting with the primitive adaptive tutoring systems and moving to the present-day models with the ability to maintain coherent academic discourses, noting that the pace of technological development has always been faster than the evolution of pedagogical principles. Wang et al. (2026)1 recently carried out a scoping review of the subject of AI in language learning and the legitimization of generative tools as a qualitative novelty in the area, and in the process of its creation, they do not discover any ready-to-use information but create new content. The technological adoption system in the South Punjab case in particular is more of a pragmatic approach to the structural issues such as large student/faculty ratio, lack of library purchasing and the geographical remoteness amidst other big academic centers. Generative AI will help in providing education in this environment with critical structural gap.

Not without complications, however, is this dynamic. Cotton et al. (2024) have reported the negative impact of intensive use of AI on the skills of students to develop arguments independently. According to Risko and Gilbert (2016), the so-called cognitive offloading, or the process of externalizing the cognitive functions to the work of technological machines, was something that added to the loss of the very cognitive functions that it was supposed to facilitate more and more. When it comes to ESL students being engaged in the study of literature, where the main objective is the cultivation of a distinct critical voice, delegation of analysis exercises to language models poses a great threat to the basic learning outcomes.

1.2 The Statement of the Problem

Despite the fact that the use of AI tools is common among university students in South Punjab, there are few empirical studies that explore this phenomenon. The previous literature usually considers AI as a broad classification, which does not consider significant differences in the way students approach various platforms. ChatGPT may be used as an example when a student has to write a lengthy academic paper, Meta AI may be used when a student wishes to engage in a dialog, and Google Gemini may be used when a student wishes to pose a scientific inquiry. This is not possible in terms of aggregate institutional policies in such functional nuances. In addition, the literature lacks information about the magnitude of AI use in South Punjab context. The institutional evaluations often deceive a student who uses AI to create complete essays with the student who has never heard of such applications, thus, masking the differences in risks and learning between the two that are of great magnitude. Baidoo-Anu and Owusu Ansah (2023) believe institutional interventions should be successful, which requires both platform-specific and intensity differentiated data. This gap in the existing empirical literature is filled by the current study, which will present a statistical analysis of student perception in a single context (South Punjab in Pakistan).

1.3 Research Objectives

The research is informed by the following four objectives:

1. To determine the particular AI tools that ESL students resort to in South Punjab universities, as well as to examine trends in preference.
2. To categorize students based on their frequency of AI use — frequent, occasional, or unaware — and to find out how many students are in each category.
3. To determine how students think AI-assisted learning will be beneficial and how to chart the range of engagement between strong dependence on AI and over-reliance.
4. Multiple regression analysis to determine predictive relationships between patterns of AI use, constructs of reliance and self-reported ESL learning outcomes.

1.4 Research Questions

The study was undertaken in the following research questions:

RQ1: What are the current trends of AI tools in ESL students of South Punjab universities?
RQ2: What are the distributions of the students on the three levels of the intensity of AI usage?
RQ3: How usefully do students use AI tools and in what areas may the productive scaffolding and over-dependence meet?
RQ4: Do trends in the use and preference of AI tools and precursors of ESL learning outcomes?

1.5 Hypotheses

The following hypotheses were to be tested empirically:
H1: There are positive and significant connections in the use of AI tools, in this instance, ChatGPT, to ESL learning outcomes.
H2: Academic learning behaviors are negatively related to over-reliance on AI tools.
H3: The academic achievement of students utilizing ChatGPT most of the time is considerably greater than that of students using other AI tools.

2. LITERATURE REVIEW

2.1 Evolution of AI Tools in ESL Education

The development of AI-assisted pedagogy in language teaching has been quicker. Initially released in the 1990s in the form of grammar-correction tools, the AI technology has evolved over the last thirty years to be able to produce complex and stylistically diverse prose in real-time (Zawacki-Richter et al., 2019). A 20-year empirical review by Wang et al. (2026) suggested that this has completely transformed the interaction of learners with written text and redefined them as other than passive participants in feedback; as active co-creators of meaning. This shift is significant to ESL learners, and language production can be an essential issue of anxiety. Any resources that can lessen the burden of cognitive processes, without affecting learning outcomes, are thus highly pedagogical.
ChatGPT has turned into the most prevalent AI-assisted writer in the scholarly writing of undergraduates nowadays (Farrokhnia et al., 2023). It is especially skillful at the demands of literature coursework, because of its capacity to generate coherent and fluent long prose. Meta AI, in its turn, is closely related to conversational practice, and is deployed in the popular social apps (Tlili et al., 2023), yet Google Gemini is an information-seeking engine that has some conversational functionality (Wardat et al., 2023). According to Holmes et al. (2022), such functional differences have a pedagogical implication since students can have vastly different views of the social role of a tool and how it is used in academic life. The percentages of the usage of ChatGPT in the present study align with the situation on the global level: Lim et al. (2023) who surveyed 1,354 students in Southeast Asia reported that the usage of ChatGPT in terms of academic writing assignments was at 76 percent of the population, which is also closely similar to the findings of Farrokhnia et al. (2023), who surveyed these inclinations are more of a South Punjab statistic, but the specific dependency forms brought about by structural resource deficiency are more academically of interest.

2.2 Technology Acceptance in Resource-Constrained Contexts

A theoretical concept about the perception of technology adoption and resistance pattern was offered by the Technology Acceptance Model (TAM) which originally had been suggested by Davis (1989). The main hypothesis of the model that perceived usefulness and perceived ease of use are the key factors affecting adoption have proved to be true in a wide scope of empirical settings. It was later expanded by Venkatesh et al. (2003) to the Unified Theory of Acceptance and Use of Technology (UTAUT) and included the social influence and facilitating conditions as other predictors. This broadened model has been used since to study the learning management systems, mobile devices, and AI tools (Farrokhnia et al., 2023).
The case with South Punjab is a special application of TAM. Perceived usefulness, in this case, is more than convenience: when a student cannot find a needed text in library collections or cannot access the subscriptions that the institution has, an AI tool is not merely useful but an essential part of its functionality. TAM is able to explain this first adoption. But it is not comprehensive insofar as the post-adoption stage where technology can be scaled up to a cognitive scaffold to a

cognitive substitute wherein the learners do not engage in a productive struggle that is deep learning.

2.3 Strong Reliance, Over-Reliance, and Cognitive Divesting

Theoretically, there is a difference between two forms of AI engagement, strong reliance and over-reliance. Strong reliance can entail AI as a scaffold, e.g. a draft to comment on, find the vocabulary that is relevant, or a sketch to ask questions and elaborate on. The intellectual author of the work in this mode is the student. Over-reliance operates differently. Risko and Gilbert (2016) distinguished cognitive offloading as the methodical out of mind transfer of mental work to external equipment whereby the capability and the drive to perform the mental work autonomously by the individual is gradually diminished.

This difference bears especially significant implications in the humanities, where cultivation of an original voice of analysis is one of the main educational objectives. Bender et al. (2021) postulated that big language models do not produce reasoned text, but statutorily plausible text. By posting literature analysis that was produced by AI, a student not only has violated the principles of academic integrity, but has also avoided the development process that the evaluation was designed to facilitate. Cotton et al. (2024) connected this dynamic directly to academic integrity issues, claiming that AI-created text can deprive students of the learning experiences inherent in composition. Eaton (2023) accentuated the respective necessity of the institutional structures capable of differentiating between AI as scaffolding and AI as replacement.

2.4 Benefits of AI-Assisted Learning for ESL Students

The AI tools in the case of South Punjab close the perennial and much-publicized gaps in education resources. Literary criticism, model analysis and scholastic comment are severely deficient in the provincial universities compared to the metropolitan ones. In such locations as Bahawalpur, Multan and Dera Ghazi Khan, a sort of AI-generated critical response or essay format, is a compensatory instrument to structural inequality, rather than an academic luxury. Chang and Sun (2024) in a systematic review of AI-assisted language learning have found out that AI-generated formative feedback positively influences self-regulated learning, enhancing students with the capability to monitor, evaluate, and adjust their language production. Zawacki-Richter et al. (2019) also added that individualized learning experiences are promoted by AI tools at a scale that is barely achievable in the conventional classroom environment. The AI may also be applied to the affective barriers that do not allow the production of the second language in first-generation university students with high language anxiety levels.

2.5 The AI Literacy Divide

The focal concept to interpret the stratified results in the present study is the AI literacy divide. The notion of technology being a democratizing force is a widely-known theory, but Selwyn (2019) cautioned that technological adoption trends tend to reproduce, rather than eradicate, the existing social inequalities. The gap in frequency between simple users and unaware users, which was detected in this study is not merely a skills gap; it is an access gap to the scholarly discourse that AI is changing. This kind of unequal distribution of digital capital implies that, unless institutional efforts are specifically directed at mitigating such differences in performance, then such differences are likely to continue to grow, at the cost of students who are already marginal to the academic life.

2.6 Methodological Considerations in Educational Technology Research

Quantitative studies involving educational technology may apply descriptive and correlational designs which are applied in order to follow the pattern of behaviors and examine the connection between variables without the aim of identifying the cause and the effect. The descriptive statistics will provide a cross-sectional description of the current behaviors, both in frequency and in the shape of the AI tool use. Pearson correlation and multiple regression (such as correlational analyses) helps researchers to test directionality and strength of the relationship between constructs, such as the relationship between AI reliance and academic

performance. These methods are the traditional way of generating initial evidence where minimal has been researched, identify trends that can be subsequently experimented or longitudinally tested. They particularly best suit heterogeneous populations such as the university students, where it is barely possible to fully control variables.

2.7 Academic Integrity in Higher Education

The dissemination of AI-composed text has added novel intricacies to the enforcement of academic integrity. Though technically, AI-generated content may not be picked up by plagiarism-detecting software because the content may appear to be original, it breaks the key principle of academic work because it is a manifestation of intellectual activity by a student. Eaton (2023) proposed a taxonomy of AI-assisted misconduct, which added a continuum, one end of which is brainstorming with the assistance of AI and the other end is giving the task of writing an assessment. Most of the students fall somewhere in the range. Baidoo-Anu and Owusu Ansah (2023) asserted that the overall prohibitions are ineffective in such a case as South Punjab where AI use has already become an institutional element of the educational process of students. They, instead, advance AI-conscious pedagogy, which is specifically formed as ethical and reflective working with such tools.

2.8 Theoretical Framework

The Technology Acceptance Model (TAM) which was first proposed by Davis (1989) forms the basis of this study. The assumption behind this model is that two important perceptions influence a decision by an individual to adopt a technology; perceived usefulness and perceived ease of use. Although TAM has been commonly used in research of educational technologies, there is a lack of research on the application of TAM to generative AI in ESL learning in non-Western semi-urban settings. The current research aims at filling this gap by generalizing TAM to a scenario where perceived usefulness intersects with cognitive dependency, the aspect, which was not considered in the original version of the model. This extension is three times the theoretical. Pedagogy The study will offer the educators of South Punjab the initial empirical mapping of the AI tools that are utilized by their students as well as the level to which they have been utilizing the tools. On the policy front, it offers a statistical support of developing AI-use policies that are responsive to the dynamics of the developing-region university rather than applying models of more endow institution. In theory, it contributes to the value of TAM since it describes the process through which the perceived usefulness turns into the cognitive dependency by the lack of resources.

3. METHODOLOGY

3.1 Research Design

The study design was a quantitative descriptive-correlational. This design was selected as it enables to systematically describe the AI usage patterns and investigate the relations between these patterns and learning outcomes without the experimental controls to cause the inferences. Descriptive statistics were used to describe the sample and usage behavior of the sample, Pearson correlation was used to explore the bivariate relationship between variable, and multiple linear regression was used to identify the independent predictors of the outcome variable.

Regression Assumptions (reported in §3.4): Prior to analysis, the assumptions of linearity, normality of residuals, and homoscedasticity were verified using IBM SPSS v25.0. Results supported the appropriateness of the multiple linear regression model.

3.2 Population, Sample and Sampling Rationale

The target population included undergraduate ESL and English Literature students in South Punjab public sector universities in the 2024–2025 academic year, Pakistan. A convenience sampling was utilized to sample 100 students in three institutions. The practicalities of the research in South Punjab, including inaccessibility of the institutions and inability to achieve administrative cooperation, predetermined this method. The convenience sampling does decrease the extrapolability of the findings; however, the sample size is adequate to perform the intended analysis. When there are few predictors and moderate-large effect sizes, a sample of 100 is adequate to

do a multiple regression analysis (Cohen et al., 2018).

Sampling Rationale Note: While convenience sampling constrains generalizability, this method was the only feasible approach given documented access barriers in South Punjab public universities. Findings should be interpreted as exploratory within this specific context.

Table 1: Participant Demographic Profile (N = 100)

Demographic Variable	Category	N	%
Gender	Male	60	60.0
	Female	40	40.0
Year of Study	Semester I–IV	50	50.0
	Semester V–VIII	50	50.0
Institution Type	Public University	100	100.0

Note. All participants were enrolled at public universities in South Punjab. Gender and year of study were self-reported.

3.3 Instrumentation

The structured, self-administered questionnaire created by the research team was used to collect data. To determine content validity, three faculty members (experts in the field of linguistics, ESL pedagogy, and educational technology) reviewed the instrument. Wording refinements were done following a pilot test based on their reviewer feedback. The last scale contained 25 items which were grouped into four subscales:

5. Preference and Demographics of the Tool (5 items).
6. Usage Intensity (5 items).
7. Perceived Benefits and Reliance Spectrum (15 items), broken down into three 5-item subscales: Non-Reliance, Strong Reliance, and Over-Reliance.

They were all assessed on a five-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree). Measures of internal consistency were done with Cronbach's alpha at subscale level: Strong Reliance (α = .84), Over-Reliance (α = .87) and Non-Reliance (α = .79). The instrument reliability was α = .87.

3.4 Data Analysis

The analysis of data was done using the IBM SPSS Statistics (Version 25.0). Before the regression analysis, the assumptions of linearity, normality of the residual and homoscedasticity were tested. The study was analyzed in four successive stages (1) descriptive statistics to describe AI usage patterns; (2) Cronbach's alpha to test the subscale reliability; (3) Pearson correlation to test the association between two variables; and (4) multiple linear regression to establish the predictive ability of ChatGPT preference, Strong Reliance, and Over-Reliance on self-reported academic outcomes.

3.5 Ethical Considerations

The ethical guidelines of the institution were followed to the letter in carrying out the study. They never had to participate and no academic consequences of rejection or dropping out. No personally identifiable information was obtained or kept; anonymity was observed during the whole time of the study. All the participants signed an informed consent before the data were collected. The data obtained in the surveys is stored in password-protected institutionally-protected servers within five years according to the regular data governance practices of academics.

4. RESULTS

4.1 AI Tool Preferences

The findings show that there is a strong platform adoption hierarchy. The most common tool described was ChatGPT, with 80 percent of the study participants indicating that they used it (Table 2), and the third and the fourth were called Meta AI and Google Gemini (15 and 5 percent, respectively). None of the other platforms were found to be key tools. This hegemony concurred with the result of Lim et al. (2023) in Southeast Asia (76%) and Farrokhnia et al. (2023) in a world sample. The reality that 80 percent of the ESL students in a

region which has no formal AI policy have come together on a single proprietary platform indicates that the academic culture is naturally structuring itself around technologies which the institutions have not approved or controlled.

Table 2: Distribution of AI Tool Preference Among ESL Students (N = 100)

AI Platform	N	%
ChatGPT (OpenAI)	80	80.0
Meta AI (Meta Platforms)	15	15.0
Google Gemini (Google DeepMind)	5	5.0
Total	**100**	**100.0**

Note. Respondents selected the single AI platform they used most frequently for academic activities.

4.2 AI Usage Intensity

Table 3 indicates how intensively the AI has been used among the sample. The majority of the students (70% of the students), were Frequent Users, who use AI tools on a daily or weekly basis, in an academic context. The sample included Occasional Users (20%), and Unaware or Unskilled (10%). This dissemination corroborates the extensive adoption of AI-related tools in the academic practice and, at the same time, outlines a serious issue of digital exclusion that impacts a small portion of students.

Table 3: AI Usage Intensity Among ESL Students (N = 100)

Usage Intensity Category	n	%
Frequent Users (daily/weekly academic use)	70	70.0
Occasional/Irregular Users (sporadic, unfocused)	20	20.0
Unaware/Unskilled Users (minimal AI experience)	10	10.0
Total	**100**	**100.0**

Note. Classifications are based on self-reported frequency and proficiency of AI tool use.

4.3 Descriptive Statistics: Reliance Spectrum

The descriptive statistics and reliability coefficients of the three reliance constructs are shown in Table 4. The highest mean score was given to Strong Reliance (M = 4.10, SD = 0.65), which implies that students have a high agreement with the idea that AI is a valid academic scaffold. Nevertheless, the mean of Over-Reliance (M = 3.85, SD = 0.72) was also quite high, which means that the boundary between successful scaffold and the harmful dependency is very narrow. The items that exhibit such behaviors as giving unedited AI-generated text and experiencing anxiety when writing without AI assistance contributed to this score. The mean (M = 2.40) of Non-Reliance was the lowest, which proves that the independent academic work is done without the assistance of AI and has become the exception rather than the rule among this population.

Table 4: Descriptive Statistics and Internal Reliability for Survey Constructs (N = 100)

Construct	Items	M	SD	Alpha	Range	Interpretation
Healthy Reliance	5	4.10	0.65	0.84	1–5	High Agreement
Over-Reliance	5	3.85	0.72	0.87	1–5	Moderately High
Non-Reliance	5	2.40	0.85	0.79	1–5	Low Agreement

Note. M = Mean; SD = Standard Deviation; Alpha = Cronbach's Alpha. A mean of 3.0 represents a neutral response.

4.4 Correlation Analysis

The Pearson correlation analysis showed that there is a strong positive correlation between Frequent AI Usage and Perceived Benefits ($r = .68$, $p < .01$). Positive relationship between Over-Reliance and Frequent Usage also had ($r = .55$, $p < .01$) relationship. The intersection makes the Performance-Dependency Paradox

true: the students, who actively engage in the use of AI tools, are the ones most vulnerable to dependency. This result conforms to the theoretical apprehensions that Cotton et al. (2024) and Bender et al. (2021) have about the cognitive costs of offloading critical thinking to AI systems.

4.5 Multiple Regression Analysis

Composites of self-reported academic outcomes of students were regressed on three predictors; ChatGPT Tool Preference, Strong Reliance, and Over-Reliance. The overall model was statistically significant, $F(3, 96) = 45.12$, $p < .001$, and had a 52 percent variance in the outcome variable ($R^2 = .52$, Adjusted $R^2 = .51$). Table 5 shows the entire regression coefficients. ChatGPT Tool Preference was found to be the best positive predictor ($\beta = .62$, SE = .09, $t = 6.85$, $p = .001$) and it proved H1. Strong Reliance was also a significant positive predictor ($\beta = .35$, SE = .10, $t = 3.42$, $p = .001$). On the other hand, Over-Reliance was a major negative predictor ($\beta = -0.31$, SE = .10, $t = -3.10$, $p = .002$) which validated H2. These findings suggest that platform preference, and a positive interaction with AI can have a positive impact on academic performance, however, the trends of behavior in relation to dependency have a negative effect on performance that is quantifiable.

Table5: Multiple Linear Regression: Predictors of ESL Learning Outcomes (N = 100)

Predictor	Beta	SE	t	p	Sig.
ChatGPT Tool Preference	0.62	0.09	6.85	< .001	Yes
Healthy Reliance	0.35	0.10	3.42	.001	Yes
Over-Reliance	−0.31	0.10	−3.10	.002	Yes

Note. Beta = standardized beta coefficient; SE = standard error. $R^2 = .52$, Adjusted $R^2 = .51$, $F(3, 96) = 45.12$, $p < .001$. The outcome variable is a composite score of self-reported academic performance.

5. CONCLUSION

5.1 Findings

The results provide an in-depth picture of the implementation of AI in a resource-limited learning environment. ChatGPT (80%) prevalence indicates global trends in adoption but within the area, it is more significant because of structural need. ChatGPT is an educational lifeline, a compensatory system that closes the content coverage gaps in provision in universities that do not have adequate library support infrastructure, faculty office hours, and peer support infrastructure.

The significant pedagogical challenge is also the three-level stratification of users — Frequent, Occasional, and Unaware. The single institutional policy of AI is not likely to work well since it would have to concern three groups of people having a fundamentally different set of needs, behaviors, and risks. Regular users need to be instructed on how to differentiate between beneficial scaffolding and intellectual substitution. Rarely used users need a plan to be more conscious and intentional in incorporating AI. The ignorant students should be given the minimum digital literacy to ensure that they are not sidelined further. Of particular interest is the 10 percent unaware population: these students are literally being barred out of the technological experiences that define the academic life of their peers, and unless something is specifically done about it, such barring is likely to further widen already existing inequalities.

The most significant finding is that, the score of high Strong Reliance and high Over-Reliance are co-occurring. The two means are similar ($M = 4.10$ vs. $M = 3.85$), which means that it is a slow process that is difficult to self-report becoming a problematic dependency after participating in constructive AI activities. Students who initially are deliberate scaffolders can gradually reduce the degree of cognitive load they require to learn as they become more familiar with AI-generated output. The regression results can quantitatively support this interpretation: the negative standardized beta of Over-Reliance ($\beta = -0.31$) allows concluding that even the behavioral patterns that can be observed to boost performance in the short run may harm the academic progress in the long-run.

5.2 Recommendations

The following are the recommendations of the present study:

1. Shift Beyond Blanket Prohibition: Institutional responses are to make a switch beyond blanket prohibitions of the use of AI, which is not practicable in view of the structural dependence of students on the use of such tools. Instead, colleges should make investments in AI-conscious pedagogy, which teaches them to employ AI to support writing processes in brainstorming, outlining, and drafting, but not to critical thinking.

2. Redesign Assessment Practices: Assessment ought to be redesigned in a way that reduces the likelihood of cognitive offloading. In-class writing assignments, oral presentation of work turned in and a multi-stage writing to the draft can all help ensure that AI is indeed a supportive rather than a substitutive agent.

3. Fill the Digital Divide: Interventions such as introductory AI literacy classes and integrated digital skills training should be implemented to address the 10% of students who are not yet familiar with such tools, to avoid the growing inequality gap.

4. Implement Ethical Frameworks: There should be clear and operationally feasible guidelines that assist students, teachers and administrators identify the difference between strong reliance and over-reliance to ensure that the integrity of the study of literature and the development-related results of the learning process are not jeopardized.

5.3 Future Research Directions

The current research has a few limitations which result in fruitful research directions in future. To begin with, stratified random sampling over a wider scope of institutions in South Punjab is necessary in order to build up population-level baselines and in order to be able to generalize meaningfully. Second, longitudinal studies following the same group throughout a school year are needed to determine the changes in AI dependence patterns over time and in what circumstances strong engagement is transformed to over-dependence. Third, an in-depth interview and think-aloud protocol mixed-method design would provide the qualitative depth that would be required to interpret the statistical trends found here, to learn which reasoning and motivations, specifically, are driving the behaviours of students towards the adoption of AI.

5.4 Conclusion

The present study presents the results of the two-sidedness of AI application in higher education in South Punjab. ChatGPT, and similar applications, are now virtually unfeasible to engage in academics in a resource-restricted environment. But this inseparability comes with the risk of the Performance-Dependency Paradox: the same things that make academic advancement possible can also pose a threat to the independent thought processes that higher education is supposed to foster. When applying TAM to the context, it would prove that perceived usefulness when it is affected by structural scarcity may turn blurred with cognitive dependency unavailable in the original model. Although the generalizability of the findings of the current study is inevitably limited by the convenience sample used, it offers a good empirical base on a region where this kind of data have been mostly lacking. The response to this is not to confront these technologies but to seek the pedagogical genius to exploit them to enlarge and not to constrict intellectual capacities of the students.

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